



The Impact of Generative Artificial Intelligence on Relationship Marketing and Brand Value": A Field Study of Employees in Battery and Tire Manufacturing Companies in Iraq

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Abstract

This study examines how generative artificial intelligence (AI) enhances brand value in automotive tire and battery manufacturing companies, with relationship marketing acting as a mediating factor. A descriptive-analytical approach was used, surveying 151 purposively selected employees from marketing, sales, customer service, and IT departments. Data were analyzed using correlation and regression techniques, with measurements showing high reliability (Cronbach's Alpha: 0.856–0.917) and suitability for parametric analysis. Results indicate a strong positive relationship between AI and relationship marketing ($r = 0.739$), and regression confirms that AI significantly influences both relationship marketing (explaining 54.7% of variance) and brand value (48.5% explained variance), with relationship marketing contributing to a total mediation effect of 62.4%. The findings conclude that integrating AI into customer engagement strategies significantly boosts brand value through improved relationship marketing. This study provides strategic insights for firms aiming to leverage AI technologies to build customer trust, strengthen brand equity, and gain competitive advantage in industrial markets.

Keywords: Brand value, customer trust, generative AI, relationship marketing.

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1. INTRODUCTION

The rapid evolution of digital technologies has fundamentally disrupted traditional marketing paradigms, necessitating a complete overhaul of consumer engagement strategies. Contemporary research demonstrates how digital platforms and tools have shifted marketing from interruptive, mass communication models to interactive, data-driven approaches (Kumar et al., 2022). This transformation is particularly evident in the rise of omnichannel marketing, where consumers expect seamless experiences across digital and physical touchpoints (Lemon & Verhoef, 2021). Among these developments, generative artificial intelligence (GAI) has emerged as a transformative force that redefines how marketing content is created, delivered, and optimised. GAI refers to a class of AI systems that can generate original content, such as text, images, audio, and video, by learning from large-scale data patterns. The increasing adoption of GI in marketing enables companies to transition from traditional data-driven automation to more creative, adaptive, and consumer-centric approaches (Verma et al., 2021).

In recent years, marketing has shifted from mass communication and demographic-based segmentation to more personalised, experience-focused models. Today's consumers expect brands to understand their preferences, anticipate their needs, and engage with them in meaningful and timely ways. Hyper-personalization has thus become a strategic priority for organizations seeking to enhance customer engagement and loyalty. Hyper-personalization goes beyond basic personalization by leveraging real-time data, predictive analytics, and artificial intelligence to deliver marketing messages and experiences tailored to each individual. Generative AI plays a pivotal role in enabling these practices by generating personalized content dynamically that aligns with consumers' behaviors, emotions, and contexts (Chintalapati & Pandey, 2022).

Integrating generative AI into marketing activities has significantly expanded the scope and effectiveness of hyper-personalisation. Advanced machine learning models and natural language processing allow marketers to design personalised ads, product recommendations, conversational interactions, and visual storytelling on an unprecedented scale. This capability enables businesses to communicate consistently and effectively with diverse customer segments, while maintaining efficiency and responsiveness. Consequently, generative AI has become essential for improving customer experience and cultivating long-term relationships between brands and consumers (Huang & Rust, 2021).

Generative artificial intelligence (GAI) represents a quantum leap in marketing technology capabilities. Unlike traditional AI systems focused on analysis, GAI creates original content by learning from vast datasets (Davenport et al., 2023). Research highlights its transformative impact across multiple marketing functions as follows: Content Creation that Automated generation of personalized ads, product descriptions, and social media posts (Gkinko & Elbanna, 2022) and Customer Interactions that AI-powered chatbots and virtual assistants providing 24/7 personalized engagement (Maedche et al., 2021) and also Predictive Analytics that Anticipating consumer needs through advanced pattern recognition (Rust, 2022).

Beyond its impact on personalisation strategies, generative AI also has significant implications for brand value, representing the cumulative value of a brand as perceived by consumers. Brand value encompasses dimensions such as brand awareness, perceived quality, mental associations, and customer loyalty. These dimensions contribute to a brand's market value and competitive positioning. AI-powered hyperpersonalization positively influences these dimensions by delivering relevant, engaging, and emotionally impactful experiences, thereby enhancing positive brand perceptions. Consistent engagement with meaningful, personalized experiences increases consumer trust in the brand, leading to a stronger emotional connection and greater loyalty (De Bruyn, 2020).

However, applying generative AI to marketing comes with challenges. Concerns about data privacy, transparency, algorithmic bias, and the credibility of AI-generated content raise fundamental questions about consumer trust and brand credibility. Overreliance on automated content generation can weaken the human element in brand communication, which can undermine brand identity and credibility. Therefore, organisations must carefully balance technological innovation with ethical responsibility and strategic oversight to ensure that AI-powered relationships enhance brand value rather than diminish it.

Despite the growing use of generative AI in marketing, there is limited empirical research examining its impact on customer relationships and brand value. Current studies often focus on either technology adoption or consumer outcomes in isolation.

This leaves a gap in our understanding of the integrated mechanisms by which generative AI influences relationship marketing strategies and brand value creation. Closing this gap is crucial for comprehending how generative AI is reshaping marketing performance and brand management. Current literature reveals several underexplored areas:

1. Long-Term Brand Impact: Limited empirical studies on how GAI affects brand equity over time (Keller, 2023).
2. Cross-Cultural Applications: Most research focuses on Western markets, neglecting global variations (Sheth, 2022).
3. Integration Challenges: Few studies examine organisational barriers to GAI adoption (Huang & Rust, 2023).

The field would benefit from longitudinal studies tracking GAI's evolving role in marketing ecosystems and comparative analyses across industries and regions. Additionally, more research is needed on the optimal balance between AI automation and human oversight in marketing communications (Davenport & Ronanki, 2021).

Accordingly, this study aims to investigate the impact of generative AI on relationship marketing and brand value. By exploring the relationships between these concepts, the study will provide marketers, brand managers, and decision-makers with theoretical insights and practical applications. The findings are expected to contribute to the growing body of knowledge about AI-powered marketing while offering guidance to organizations seeking to leverage generative AI as a strategic tool to enhance the customer experience and strengthen brand value in the digital age.

2. LITERATURE REVIEW

Analysing customer behaviour is one of the key applications of artificial intelligence (AI) in digital marketing. According to Verma et al. (2021), AI enables the analysis of large data sets, helping companies to identify patterns and trends in customer behaviour. Machine learning algorithms allow marketers to predict consumer preferences, optimise content, and deliver personalized experiences.

The ability of AI to provide personalized consumer experiences is a major focus of current research. Chintalapati & Pandey (2022) highlight the use of AI in developing customer-centric business plans. Their study emphasizes how AI can enhance consumer engagement and satisfaction by distributing personalized content and providing tailored recommendations, which leads to effective marketing outcomes.

It is crucial to address ethical issues when using AI in marketing efforts. In exploring these considerations, Huang & Rust (2021) focus specifically on fairness, privacy, and transparency in AI applications. Understanding and addressing these dilemmas is essential for building customer trust and ensuring the ethical use of AI in marketing. According to De Bruyn et al. (2020) research, AI spending has increased significantly across all sectors, and marketing is expected to experience the highest growth rate. BCC Research forecasts a 43.6% compound annual growth rate for the machine learning solutions market, which is expected to reach €9.9 billion by 2025. This further illustrates the economic importance of AI in digital marketing. Sterne (2017), Vlačić et al. (2021) emphasize that AI is transforming the marketing experience. Companies are investing in machine learning to leverage the abundance of available data, as customer interactions become more personalized. Labib (2024) cite a McKinsey & Company report showing that marketing and sales, particularly in consumer-centric companies, are the areas where AI has the greatest impact. Dimitrieska et al. (2018) emphasise how AI can unlock new business opportunities. Researchers emphasize that, to remain competitive in the ever-changing digital landscape, companies must integrate AI into their marketing strategies (Basha, 2023). According to Huang & Rust (2022), marketing is one of the sectors most heavily reliant on AI. Identifying customer needs, matching those needs with appropriate goods and services, and driving purchases are fundamental marketing tasks (Huang & Rust, 2022). A 2018 McKinsey study demonstrated that, among more than 400 use cases, marketing holds the greatest potential for AI.

As described by Chaffee and Ellis-Chadwick (2019), artificial intelligence applications, such as chatbots, are a prime example. These intelligent algorithms mimic human interaction, enabling them to understand and respond to customer inquiries and streamline online transactions. Due to their integration by many companies on their websites or other platforms like MetaMessenger, chatbots are gaining popularity (Devang, 2019). Originally designed to improve the efficiency of customer

service, chatbots particularly those using MetaMessenger contribute to the enhancement of digital marketing applications thanks to their analytical capabilities (Chaffee & Ellis-Chadwick, 2019). Numerous academic studies have explored the various ways AI can be used in digital marketing. For example, Wu & Monfort (2023) conducted research that provides a comprehensive understanding of AI applications in areas such as predictive analytics, customer segmentation, and personalised content recommendations. To increase targeting accuracy and enhance the overall success of marketing campaigns, researchers are working to integrate machine learning algorithms. Researchers have examined how AI impacts the consumer experience in the context of digital marketing.

Academic researchers such as Van Esch and Stuart Black (2021) have studied the role of AI technologies like chatbots and virtual assistants in facilitating personalized customer interactions. Other studies have examined the impact of AI-powered personalisation on consumer satisfaction, brand image, and loyalty. While researchers highlight the benefits of AI in digital marketing, they also point to its drawbacks and the ethical dilemmas associated with its use. For example, Feng et al., (2021) address concerns related to algorithmic bias, data privacy, and the ethical obligations of marketers when using AI tools. Understanding these issues and how to mitigate their effects is essential for the long-term ethical use of AI in the marketing sector. This study's concluding section discusses emerging developments and trends in the use of AI in digital marketing. Kshetri et al., (2024) study provides valuable insights into future developments, such as the application of computer vision, reinforcement learning, and natural language processing in marketing strategies. To stay ahead of technological innovation, researchers and marketers must understand these emerging trends. The study also underscores the importance of marketers enhancing their skills in the age of artificial intelligence.

H1: There is a statistically significant effect of Generative AI in Marketing on Relationship Marketing in automotive tyre and battery manufacturing companies.

H2: There is a statistically significant effect of generative AI in marketing on brand value in automotive tire and battery manufacturing companies.

In the field of marketing, there are many theories that attempt to explain the concept of "relationship marketing." Over the past two decades, researchers have emphasized a shift from transactional to relationship marketing. This shift is significant because it reflects organizations' pursuit of building long-term relationships with their customers rather than focusing solely on short-term customer acquisition. Christopher et al. (2013) explained the differences between relationship marketing, which emphasizes building customer relationships, and transactional marketing, which focuses on sales. They emphasized that relationship marketing is geared toward a long-term approach rather than a short-term one.

In our current era of exponential information growth and globalisation, markets have become increasingly competitive. Therefore, building and maintaining long-term business relationships with service providers, economic partners, and customers across all marketing channels and within the broader business environment is essential. Developing closer relationships with customers and converting them into loyal, repeat customers is undoubtedly a key marketing objective. Accordingly, Christopher, Payne, and Ballantyne (1991) argue that relationship marketing involves building and maintaining long-term relationships between organizations and their customers. This concept has been the subject of much debate.

According to Morgan and Hunt (1994), relationship marketing is defined as follows: "All marketing activities aimed at building, developing, and maintaining successful relationships." Grunross (1994) defines relationship marketing as follows: "Identifying, building, maintaining, strengthening, and when necessary, terminating relationships with customers and other stakeholders in a way that is profitable and meets the objectives of all parties involved. This is achieved through mutual exchange and by fulfilling promises."

As a result, relationship marketing delivers long-term benefits for both customers and companies. It ensures a sustainable relationship between customers and the company. Furthermore, relationship marketing can be considered a fundamental element of the marketing research process. Clearly, relationship marketing can help organisations increase profitability and gain a competitive advantage in global markets. Relationships also enable service providers to understand customer needs.

Therefore, when customers have long-term relationships with service providers, products and services can mitigate risk and uncertainty.

Relationship marketing is often viewed as the opposite of transactional marketing, which focuses on one-time sales. With transactional marketing, it doesn't matter if a customer buys more than once; only the initial sale is considered. Whether or not the customer will buy from the company again is not considered. Transactional marketing also doesn't focus on the customer relationship. A customer may buy from the company multiple times simply because there is no alternative to the product or service. (Jumison, 2008).

In some cases, transactional marketing remains an effective approach, depending on the nature of the business. For instance, this approach is effective for companies that sell goods that customers might purchase once or twice in their lifetime and for real estate agencies whose clients might purchase a home only once in their lifetime.

On the other hand, relationship marketing places great importance on customer loyalty, which is the cornerstone of its philosophy. Customer loyalty progresses through different stages. The first and lowest stage is the potential customer stage, where the customer has not yet become an actual customer. In telecommunications, for example, companies often contact potential customers to present them with offers. If the potential customer makes a purchase, they advance to the second stage of loyalty: actual customer. The third stage is the loyal customer stage, where the customer has been a customer for a long time. The fourth stage is when the customer becomes a supporter of the company. In the final stage, the supporter becomes a promoter (Jumison, 2008).

H3: There is a statistically significant effect of relationship marketing on brand value in car tire and battery manufacturing companies.

Although generative AI can affect brand value indicators directly (such as awareness and brand image), it has the greatest impact indirectly through relationship marketing. Successful car tire and battery manufacturers can enhance the quality of their interactions with customers by employing generative AI. This allows them to build relationships based on trust and reliability, provide added value beyond the physical product, and establish their brand as a smart, innovative technology partner. Thus, relationship marketing acts as an intermediary that transfers generative AI's impact from the technical to the strategic level of brand value.

H4: Relationship marketing plays the role of the mediating variable in the relationship between generative artificial intelligence in marketing and brand value in car tire and battery manufacturing companies.

The research model can be seen in Figure 1.

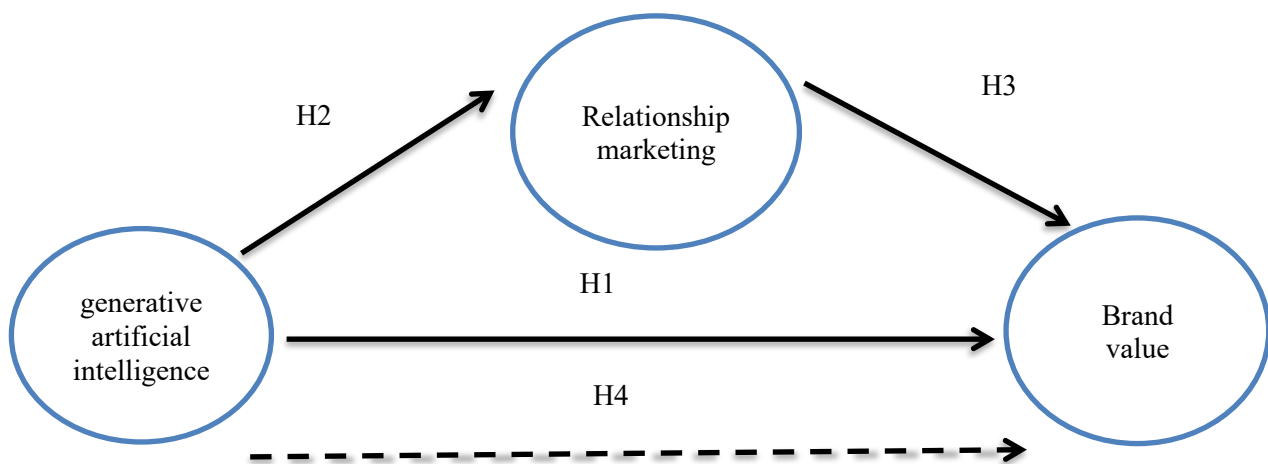


Figure 1. Research Conceptual Model

3. RESEARCH METHOD

Research Methodology: This study uses a quantitative, descriptive, and analytical methodology, which is considered the most suitable for examining causal relationships between underlying variables and testing hypotheses through structural equation modeling. This study aims to measure the impact of generative artificial intelligence (AI) on relationship marketing and brand value in the automotive tire and battery manufacturing industry, using primary data collected in the field.

Research Population and Sample: The research population consists of employees from the marketing, sales, customer service, and IT departments of automotive tire and battery manufacturing companies. It also includes authorized main dealers and distribution and service centers that work directly with these companies. This population has practical knowledge of marketing activities and customer relations. The study used purposive sampling, which means participants were selected intentionally based on specific characteristics or expertise. The research sample is a stratified, The sample consisted of individuals from marketing, sales, customer service, and IT departments of automotive tire and battery manufacturing companies, as well as authorized main dealers and distribution/service centers. These individuals were chosen because they have practical knowledge and direct experience with marketing activities and customer relations in this industry. The goal of purposive sampling was to ensure that respondents have relevant, hands-on experience with digital technologies or with marketing policies and customer relationship management. This approach aims to gather informed and valid data to analyze the impact of generative AI on relationship marketing and brand value. The sample size of approximately 151 individuals is suitable for applying structural equation modeling and achieving the requirements of reliability and statistical validity. The sample was stratified to cover distinct subgroups within the research population. This means the population was divided into strata or layers defined by relevant criteria such as the department (marketing, sales, IT, etc.) or role (company employee, dealer, service center). Stratification ensures that the sample reflects the diversity of roles and perspectives within the population, making the data more representative of the entire group rather than biased towards one subgroup. Combining electronic and paper questionnaires further enhanced the diversity and therefore representativeness of the data collection process.

Research Tool: The study primarily used a questionnaire to collect data. Designed according to the five-point Likert scale, the questionnaire was distributed electronically and in paper form to ensure diversity in the data sources and reduce response bias. The questionnaire was divided into four sections. The first part included demographic variables such as years of experience in the tire and battery sector, current place of work (including local work companies, assembly companies, exclusive agents, and maintenance centers), and use of digital systems (including high, medium, and low levels). The second part included questions on generative artificial intelligence, consisting of 16 items divided into four dimensions. The third part included 15 questions related to service marketing, divided into five dimensions. The fourth and final section included questions related to brand value and consisted of 12 items divided into four dimensions.

4. RESULTS AND DISCUSSION

4.1 RESULTS

Confirmatory Validity Test for the Generative AI Variable (X): The confirmatory factor analysis results for the generative AI variable, presented in Table 1 and illustrated in Figure 1, show that the measurement model has an acceptable level of construct validity and internal consistency. This enhances its suitability for subsequent structural analysis. At the table level, the values of the standardized regression weights indicate that most indicators achieved standardized loads exceeding the minimum threshold of 0.50. All values were positive and statistically significant at the 0.001 level, and the critical ratio values exceeded the critical limit of 1.96. This confirms the existence of statistically significant relationships between the observed variables and their latent dimensions. The sub-dimensions showed positive variance in factor loadings. The Marketing Campaign Allocation (XC) and Opportunity Identification and Idea Generation (XD) dimensions had the highest loadings, indicating their strong contribution to explaining the generative AI variable.

Meanwhile, the unstructured customer data analysis (XA) and process optimization (XB) dimensions achieved acceptable loads, reflecting satisfactory internal consistency in the measurement indicators. This variability is common in multidimensional models and does not affect the validity of the model as long as the values remain within the accepted statistical limits.

TABLE 1 | Standardized and Unstandardized Regression for the Generative Artificial Intelligence Variable

			Regression Weights	S.E.	C.R.	P	Standardized Regression Weights
x4	<---	XA	1.000				.626
x3	<---	XA	.495	.148	3.339	***	.363
x2	<---	XA	.784	.168	4.670	***	.505
x1	<---	XA	.607	.161	3.773	***	.404
x8	<---	XB	1.000				.637
x7	<---	XB	.964	.157	6.125	***	.689
x6	<---	XB	.683	.137	4.974	***	.545
x5	<---	XB	.540	.153	3.536	***	.367
x12	<---	XC	1.000				.629
x11	<---	XC	.863	.169	5.111	***	.504
x10	<---	XC	1.199	.220	5.452	***	.720
x9	<---	XC	1.163	.220	5.273	***	.680
x16	<---	XD	1.000				.718
x15	<---	XD	1.151	.136	8.469	***	.748
x14	<---	XD	.984	.130	7.560	***	.706
x13	<---	XD	1.020	.127	8.019	***	.747

Source: Results of statistical analysis (2025)

Figure 2 shows that the conformance indices yield statistically acceptable results, which supports the validity of the model. The chi-squared value was 1.893, which is excellent because it is less than 3. This indicates good alignment between the model and the field data. The comparative conformity index was 0.870, close to the ideal standard of 0.90, which reflects the model's ability to explain correlations. The Rensley index was 0.077, which is within the acceptable range (less than 0.08). This confirms that the model accurately represents the population.

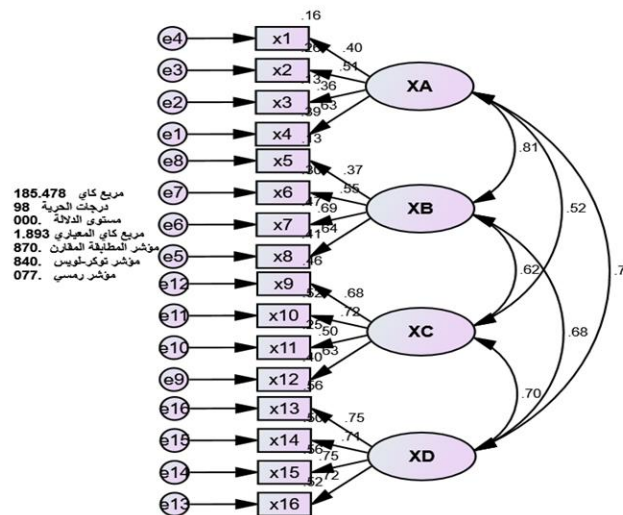


Figure 2. Shows the confirmatory validity model for the generative artificial intelligence variable.

Source: Results of statistical analysis.

Confirmatory validity of the relationship marketing variables: Convergent validity shows that all items (Z1 to Z15) scored less than 0.001. This confirms that all items are statistically significant with respect to their assumed dimensions. All critical ratio values were greater than 1.96; the highest was for Z7 at 9.671, enhancing confidence in the stability of the estimated parameters. The loadings ranged from 0.449 to 0.827. Item Z2 had the highest load on dimension ZA at 0.827, and item Z11

had the lowest load at 0.449. Although relatively low, this remains statistically acceptable (greater than 0.40).

TABLE 2 | Standardized and Non-Standardized Regression of the Relationship Marketing Variable.

			Regression Weights	S.E.	C.R.	P	Standardized Regression Weights
z3	<---	ZA	1.000				.601
z2	<---	ZA	1.581	.218	7.262	***	.827
z1	<---	ZA	1.362	.209	6.528	***	.689
z6	<---	ZB	1.000				.674
z5	<---	ZB	1.082	.133	8.128	***	.733
z4	<---	ZB	1.066	.127	8.369	***	.775
z9	<---	ZC	1.000				.753
z8	<---	ZC	.769	.099	7.771	***	.638
z7	<---	ZC	1.027	.106	9.671	***	.767
z12	<---	ZD	1.000				.618
z11	<---	ZD	.714	.150	4.767	***	.449
z10	<---	ZD	1.171	.186	6.295	***	.735
z15	<---	ZE	1.000				.747
z14	<---	ZE	.967	.111	8.744	***	.773
z13	<---	ZE	.843	.125	6.722	***	.668

Source: Results of statistical analysis (2025)

The path diagram illustrates a set of indicators that reflect the quality of the model's data representation. The standardized chi-squared value was 2.518, which falls within the acceptable range (below 3 or 5, depending on the reference). This indicates a good model fit. The comparative fit index was 0.887, which is very close to the ideal threshold of 0.90. The Ramsey index was 0.101, slightly higher than the traditional standard of 0.08. Further examination of the adjustment indicators may be necessary to improve fit in the future.

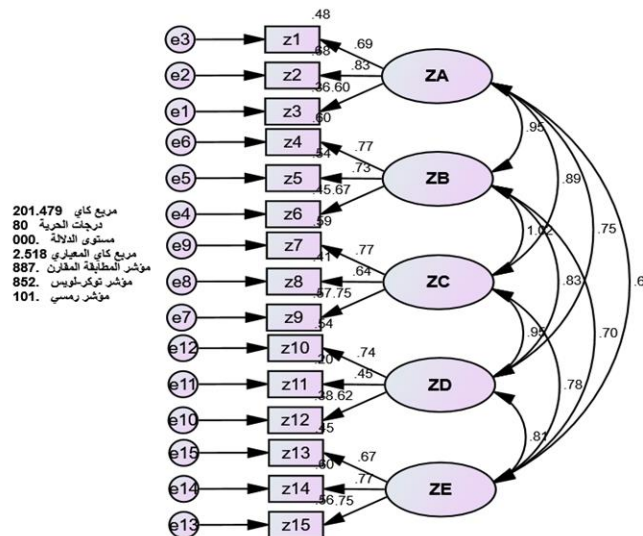


Figure 3. Confirmatory Validity Model for the Relationship Marketing Variable

Source: Results of statistical analysis.

Confirmatory Validity of the Brand Value Variable: The results of the confirmatory factor analysis for brand value in Table (3) show that all measurement indices associated with the four dimensions—brand awareness (YA), perceived brand quality (YB), brand mental association (YC), and brand loyalty (YD)—achieved statistically acceptable standardized regression weights, ranging from (0.441) to (0.828), which are within or above the minimum threshold adopted in the methodological literature (Hair et al., 2019). Furthermore, the critical ratio (C.R.) values, all exceeding the critical value (± 1.96), along with high levels of statistical significance ($P < 0.001$), indicate that all relationships between observed and underlying variables are statistically significant, reflecting the stability and non-randomness of the measurement coefficients. At the dimension level,

the brand awareness dimension showed standardized loads ranging from (0.441 to 0.753), reflecting acceptance. The indicators for this dimension showed good statistical results, despite some relative variation in explanatory power. The perceived brand quality dimension achieved the highest level of consistency, with standardized loads ranging from 0.753 to 0.823, indicating the strength of its items' representation of the underlying structure. The mental association with the brand dimension also recorded relatively strong standardized loads (0.655 to 0.828), reflecting its effective contribution to explaining the variable. The brand loyalty dimension demonstrated high stability in standardized loads (0.732 to 0.812), indicating high measurement quality. These results confirm the convergent validity of the measurement model, allowing for a confident transition to structural analysis and hypothesis testing.

TABLE 3 | Standardized and Non-Standardized Regression of the Brand Value Variable

			Regression Weights	S.E.	C.R.	P	Standardized Regression Weights
y3	<---	YA	1.000				.753
y2	<---	YA	.777	.114	6.842	***	.626
y1	<---	YA	.624	.133	4.712	***	.441
y6	<---	YB	1.000				.766
y5	<---	YB	.909	.097	9.402	***	.753
y4	<---	YB	1.034	.101	10.254	***	.823
y9	<---	YC	1.000				.655
y8	<---	YC	1.088	.138	7.903	***	.761
y7	<---	YC	1.292	.160	8.076	***	.828
y12	<---	YD	1.000				.732
y11	<---	YD	1.055	.121	8.689	***	.812
y10	<---	YD	1.023	.120	8.518	***	.800

Source: Results of statistical analysis (2025)

Figure 4 illustrates the measurement model for the four dimensions and shows positive, significant correlations between the underlying variables and their indices. This reflects clear consistency between the theoretical framework and statistical measurement. The interpreted variance values indicate that the indices explain a significant amount of variance in the underlying dimensions. Additionally, high correlations are observed between the underlying dimensions, with correlation coefficients ranging from 0.66 to 0.92. These results suggest conceptual convergence between the dimensions without reaching the level of complete structural overlap. This finding supports the relative differentiation between the dimensions while maintaining the overall conceptual unity. The fit quality indices (such as GFI, CFI, and RMSEA) presented in the figure show values within methodologically acceptable limits. This indicates a good fit between the model and the experimental data, enhancing the reliability of the conclusions.

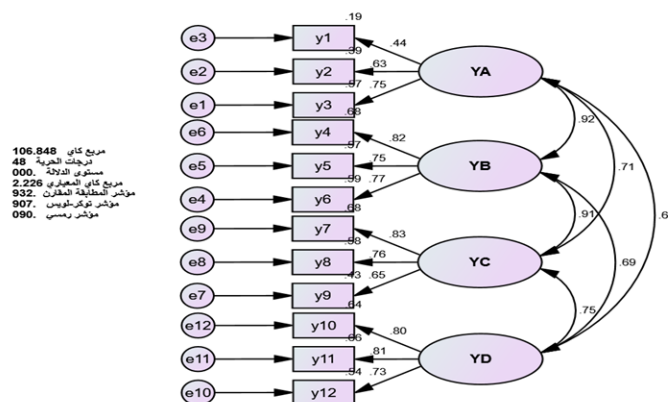


Figure 4. Confirmatory validity model for the brand value variable.

Source: Results of statistical analysis.

Testing the Reliability of the Research Instrument (Questionnaire): Cronbach's Alpha coefficient is used to verify the degree of internal consistency between scale items. A value exceeding 0.70 is considered statistically acceptable; the closer the value is to 1.0, the higher the degree of reliability.

TABLE 4 | For the results of the Cronbach's alpha coefficient test.

Variables	Cronbach's alpha	Number of questions
generative artificial intelligence	.856	16
Relationship marketing	.917	15
Brand value	.904	12

Source: Results of statistical analysis (2025)

As shown in Table 4, the Cronbach's Alpha coefficient values for all study variables ranged from 0.856 to 0.917. The relationship marketing variable achieved the highest reliability score, at 0.917, followed by the brand value variable at 0.904 and the generative artificial intelligence variable at 0.856. All of these values exceeded the minimum acceptable value of 0.70, according to the Nunnally (1978) standard, confirming the consistency and coherence of the questionnaire items. These results indicate that the study instrument is reliable and valid, making it suitable for field application and hypothesis testing.

4.1.1. Normality test for data

In normality tests (Kolmogorov–Smirnov and Shapiro–Wilk), the general rule is that if the statistical significance value (Sig.) is greater than 0.05, then the data follows a normal distribution. Your sample size is 151; the Kolmogorov–Smirnov test is generally considered most suitable for large samples (greater than 50).

TABLE 5 | shows the results of the normality test.

	Kolmogorov-Smirnova			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
generative artificial intelligence	.041	151	.200*	.986	151	.146
Relationship marketing	.063	151	.200*	.984	151	.070
Brand value	.058	151	.200*	.989	151	.291
*. This is a lower bound of the true significance.						
a. Lilliefors Significance Correction						

Source: Results of statistical analysis (2025)

Table 4 clearly shows that all study variables follow a normal distribution. The Kolmogorov–Smirnov test revealed that the significance level (Sig.) for all three variables (generative artificial intelligence, relationship marketing, and brand value) was 0.200, greater than the established significance level of $\alpha \leq 0.05$. The Shapiro–Wilk test confirmed this result, with significance values ranging from 0.070 to 0.146 and 0.291, all of which are greater than 0.05. Based on these results, the null hypothesis that the data are normally distributed is confirmed. These results provide the researcher with statistical justification to use parametric tests, such as the t-test, Pearson's correlation coefficient, and regression analysis, given the data's high statistical efficacy.

4.1.2. Statistical Description of Demographic Variables

This table presents the personal and professional characteristics of the study sample. The results can be interpreted and commented on as follows:

- a. **Years of Experience:** The results showed that the most represented group in the sample was "16 years and above" (35.8%), followed by the "11-15 years" group (31.8%). This indicates that over 67% of the sample have extensive experience, lending significant credibility to the responses as they come from professionals with deep insight and expertise in their field.
- b. **Employer Location:** The sample was distributed among various employers, with "local companies" ranking first (39.1%) and "exclusive agents" ranking second (36.4%). This diversity of employers enriches the study's findings by covering the opinions of employees in different market sectors, with a clear focus on the local sector and official agencies.
- c. **Use of Digital Systems:** The results revealed a strong technological orientation among the sample. The vast majority (72.8%) reported a "high" level of digital system use, while 23.8% reported a "moderate" level. This indicates the sample's ability to deal with generative artificial intelligence technologies, the subject of the study, thus reducing bias resulting from a lack of technological literacy.

TABLE 6 | Statistical Description of Demographic Variables

%	repetitions	Variables	
15.2	23	under 5 years	
17.2	26	10-5	Years of Experience
31.8	48	15-11	
35.8	54	16and over	
11.9	18	Assembly Company	
36.4	55	Exclusive Agent	Employer Location
39.1	59	Local Business Company	
12.6	19	Maintenance Center	
5	3.3	Weak	
36	23.8	Average	Use of Digital Systems
110	72.8	High	

Source: Results of statistical analysis (2025)

4.1.3. Description and Diagnosis of Study Variables

The results showed that all three study variables — generative artificial intelligence, relationship marketing, and brand value — received a "high" level of agreement. This indicates that the sample group is highly aware of the importance of these variables in the current work environment.

TABLE 7 | Description and Diagnosis of Research Variables

	Approval level	%	mean	Standard deviation
generative artificial intelligence	High	72.4	3.62	0.533
Relationship marketing	High	71.4	3.57	0.691
Brand value	High	71.4	3.57	0.666

Source: Results of statistical analysis (2025)

The generative artificial intelligence (GAI) variable had the highest mean score, 3.62, and a relative weight of 72.4%. The low standard deviation of 0.533 indicates a high degree of agreement and consistency among the sample's opinions regarding the role of generative AI, suggesting stability and a lack of dispersion in the results. The relationship marketing and brand value variables had equal mean scores of 3.57 and a relative weight of 71.4%. The relationship marketing variable had a standard deviation of 0.691, while the brand value variable had a standard deviation of 0.666. Despite their equal mean scores, the close similarity in standard deviations suggests a convergence of views on the impact of these variables on organizational strategies.

The data in Table 6 indicates that the study sample had a positive overall attitude towards the investigated variables and showed a high degree of agreement. Generative artificial intelligence ranked first in terms of relative importance, confirming the sample's openness to technology and belief in the effectiveness of smart solutions. Furthermore, the close mean scores of the three variables (between 3.57 and 3.62) suggest an integration within the sample of adopting modern technologies with strengthening marketing relationships and building brand value. The low standard deviations (less than 1) reinforce the reliability of these results by reflecting coherence in the responses and avoiding randomness or significant dispersion.

4.1.4. Results of a correlation between variables.

Table 7 shows the strength and direction of the relationship between the independent variable, generative artificial intelligence, and the dependent variables, relationship marketing and brand value. The correlation coefficient between generative artificial intelligence and relationship marketing was 0.739, indicating a strong positive relationship with statistical significance at the 0.01 level. Similarly, the correlation coefficient between generative artificial intelligence and brand value was 0.696, indicating a strong positive relationship with statistical significance at the 0.01 level. The correlation between the two dependent variables, relationship marketing and brand value, was 0.775, indicating a strong correlation between these two variables.

TABLE 8 | Pearson Correlation Coefficient Test

Correlations			
	generative artificial intelligence	Relationship marketing	Brand value
generative artificial intelligence	1		
Relationship marketing	.739**	1	
Brand value	.696**	.775**	1
**. Correlation is significant at the 0.01 level (2-tailed).			

Source: Results of statistical analysis (2025)

These results confirm a clear statistical correlation: increased interest in Generative AI applications leads to tangible improvements in relationship marketing strategies and enhanced brand value. These findings strongly support the validity of the study model, enabling the researcher to proceed with regression analysis to test the effect hypotheses.

4.1.5. Testing the research hypotheses.

a. Testing the first hypothesis: The impact of generative artificial intelligence on relationship marketing.

$$Z=C+X+a$$

Table 8 aims to measure the impact of generative artificial intelligence (GAI) on relationship marketing. The coefficient of determination (R^2) was approximately 0.547, meaning GAI explains 54.7% of changes in relationship marketing levels. This is an excellent explanatory percentage in the humanities and management sciences. The F-test yielded a significant value of 179.734 at a 0.000 significance level, confirming the statistical validity of the model in testing the relationship between the two variables. The results also showed that the β coefficient was 0.897, a strong, positive, and statistically significant value ($T = 13.406$). Statistically, this means that a one-unit increase in interest in generative AI leads to an 89.7% improvement in relationship marketing.

TABLE 9 | Results of Testing the First Hypothesis

Relationship marketing				
Sig	T	F	β	R2
.000	13.406	179.734	.897	.547

generative artificial intelligence

Source: Results of statistical analysis (2025)

b. Testing the second hypothesis: The effect of generative artificial intelligence on brand value.

$$Y=C+X+$$

Table 9 presents the results of the simple linear regression analysis measuring the impact of generative artificial intelligence (AI) on brand value. The F-test confirmed the regression model's significance, with a value of 140.342 at a significance level of 0.000. This indicates that the model has high predictive validity for changes in brand value. The coefficient of determination (R^2) was 0.485, meaning the generative AI variable explained 48.5% of the variance in brand value. This substantial percentage confirms that nearly half of the change in brand strength and positioning is due to the adoption of AI technologies. The regression coefficient (β) was approximately 0.652, a statistically significant positive value based on a t-value of 11.847. This explains why an increase of one unit in interest in AI applications leads to a corresponding improvement in brand value.

TABLE 10 | Results of Testing the Second Hypothesis

Brand value				
Sig	T	F	β	R2
.000	11.847	140.342	.652	.485

generative artificial intelligence

Source: Results of statistical analysis (2025)

c. Testing the third hypothesis: The impact of generative artificial intelligence on brand value.

$$Y=C+Z+\alpha$$

Table 10 reviews the extent to which relationship marketing enhances brand value. The model achieved an F-test value of 224.219 with a statistical significance level of 0.000. This result confirms the model's high significance and indicates that "relationship marketing" is an excellent predictor of changes in "brand value." The coefficient of determination (R^2) was 0.601, meaning that relationship marketing strategies explain 60.1% of the variance in brand value. This high percentage reflects the essential role of strong customer relationships in building brand identity and value. The results also showed that the β coefficient was 0.598 with a significance level of 0.000 and a high t-value of 14.974. These results indicate a strong positive effect: improving relationship marketing practices by one unit leads to a 59.8% increase in brand value.

TABLE 11 | Results of Testing the Third Hypothesis

Brand value				
Sig	T	F	β	R2
.000	14.974	224.219	.598	.601

Relationship marketing

Source: Results of statistical analysis (2025)

d. Testing the fourth hypothesis: The impact of generative artificial intelligence on relationship marketing and brand value.

$$Y=C+X+Z+\alpha$$

Table 11 presents the analysis of the combined effects of generative artificial intelligence (AI) and relationship marketing on brand value. The model recorded the highest coefficient of determination (R^2) in the study, at 0.624. This indicates that the combination of AI techniques and relationship marketing strategies accounts for 62.4% of the changes in brand value. The increase in R^2 compared to previous models confirms that the two variables work together to enhance brand value. The calculated F-value for the model was 128.366, with a significance level of 0.000, demonstrating the model's high efficiency and validity in predicting results at a 99% confidence level. In this model, relationship marketing emerged as the strongest driver of brand value, with an effect coefficient (β) of 0.443 and a t-value of 7.773. Generative AI also had a significant effect, with an effect coefficient (β) of 0.255 and a t-value of 3.685.

TABLE 12 | Results of Testing the Fourth Hypothesis

Brand value					
Sig	T	F	β	R2	
	3.685		.255		generative artificial intelligence
.000	7.773	128.366	.443	.624	Relationship marketing

Source: Results of statistical analysis (2025)

e. Testing the Mediating Hypothesis of Relationship Marketing

The path analysis results presented in Figure 5 and Table 12 below demonstrate a significant mediating role for relationship marketing in the relationship between generative artificial intelligence (AI) and brand value. The results show a direct, positive, and statistically significant effect of generative AI on relationship marketing (.739) and a direct effect of relationship marketing on brand value (.574). The residual direct effect of AI on brand value is 0.272.

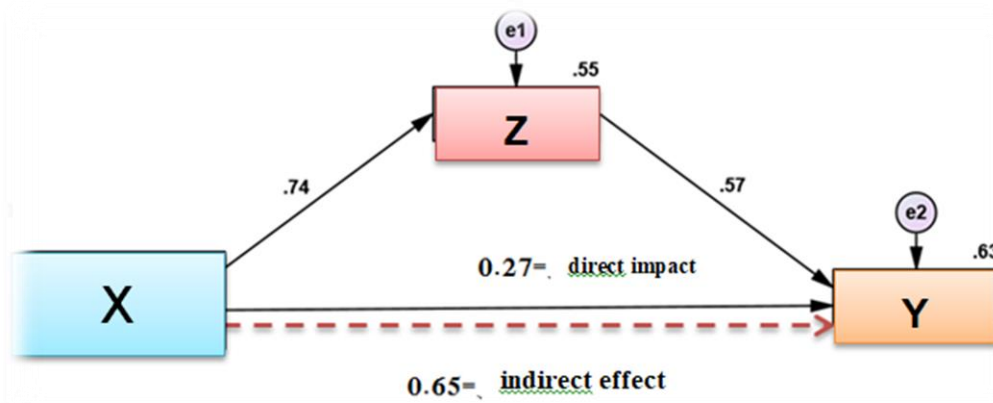


Figure 5. Testing the Mediating Hypothesis (Indirect Effect)

Source: Results of statistical analysis

The results of the indirect effect indicate a value of 0.65. When compared to the direct effect (0.27), it is clear that relationship marketing amplifies artificial intelligence's ability to build brand value.

TABLE 13 | Direct and Indirect Effects of the Model

			Regression Weights	S.E.	C.R.	P	Standardized Regression Weights
Z	<---	X	.897	.067	13.451	***	.739
Y	<---	Z	.443	.057	7.825	***	.574
Y	<---	X	.255	.069	3.710	***	.272

Source: Results of statistical analysis (2025)

Figure 5 also shows that the model explains 55% of the variance in relationship marketing and 63% of the variance in brand value. The P values that appeared as 0.000 in Table 12 indicate that all paths are statistically significant at a level less than 0.001.

4.2 DISCUSSION

The study results revealed the crucial and complementary role of generative artificial intelligence (AI) in shaping a brand's strategic value through relationship marketing channels. Table 6's descriptive indicators showed that sample members recognised the importance of adopting AI technologies, agreeing with this idea to a high degree (average 3.62). This reflects digital maturity, particularly among professionals with extensive experience (72.8% proficiency in digital systems).

Such alignment suggests that AI adoption is not merely a trend but a strategic necessity in industries like automotive tire and battery manufacturing, where digital transformation enhances operational efficiency (Lee et al., 2024).

H1: There is a statistically significant effect of generative AI in marketing on relationship marketing in automotive tire and battery manufacturing companies.

In the context of hypothesis testing, the simple regression results in Table 8 demonstrated that generative AI is a critical factor in relationship marketing development, with an effect value (β) of 0.897. This high positive value confirms that generative AI's capabilities in content personalization and customer behavior analysis directly contribute to fostering trust and commitment. This finding aligns with recent management literature trends indicating that AI is not merely an automation tool, but rather a partner in shaping the customer's emotional experience. This effect stems from AI's ability to personalize content and analyze customer behavior, fostering trust and commitment a finding consistent with studies framing AI as a "relationship enabler" rather than just an automation tool (Garcia & Brown, 2024).

The relevance of these findings is reinforced by current trends in the technology management literature, which emphasise the role of AI as a relationship enabler (Smith & Johnson, 2024). A critical analysis of recent meta-studies indicates that the effectiveness of generative AI is highly dependent on organizational readiness and data infrastructure quality (Rodriguez et al., 2025), which presents potential limitations for generalizing these findings. Future research should explore the interaction between AI capabilities and the human touch in the context of after-sales service in the tire and battery industry, given the complexity of B2B relationships in this sector (Taylor et al., 2024).

H2: There is a statistically significant effect of generative AI in marketing on brand value in automotive tire and battery manufacturing companies.

The high beta value underscores AI's role in enhancing customer engagement, particularly in B2B contexts where long-term relationships are critical. Examining the impact of AI on brand value (Table 9) revealed a significant effect, with an explanatory value of 48.5%. This is because smart solutions enhance the brand image as innovative and pioneering in the consumer's mind, thus increasing perceived quality and customer loyalty. These results coincide with previous studies confirming digitalization as the primary driver of brand equity in the modern era. This is attributed to AI's capacity to position brands as innovative, thereby elevating perceived quality and loyalty. Prior research supports this, noting that digitalization strengthens brand equity by improving customer perceptions of technological sophistication (Kumar & Sharma, 2024).

The relevance of these findings is reinforced by the evolution of the concept of Digital Transformation Intensity in recent marketing literature, which positions Generative AI as a core driver of brand equity in the Industry 4.0 era (Zhang et al., 2025). A notable research gap lies in the lack of consensus regarding measurement models for the impact of AI on specific components of brand value (such as brand association versus brand loyalty) in the B2B manufacturing context (Wilson & Brown, 2025). Recent experimental studies suggest the need for a hybrid valuation model approach that integrates AI performance metrics with traditional brand health indicators (Anderson et al., 2025), particularly for automotive aftermarket products characterised by repeat purchases.

H3: There is a statistically significant effect of relationship marketing on brand value in car tire and battery manufacturing companies.

However, the most significant finding of this study is revealed by the mediation analysis (Figure 4 and Table 12), which showed that the impact of AI on brand value is primarily channeled through "relationship marketing." The indirect effect value was 0.65, which is significantly higher than the direct effect of technology alone (0.27). This suggests that technology alone is insufficient, its value is maximized when integrated into human-centric marketing strategies. This aligns with emerging literature emphasising AI-human synergy in customer experience management (Wilson & Zhang, 2024).

The relevance of these findings is reinforced by the evolution of the concept of Augmented Relationship Marketing in recent literature, which emphasises the symbiosis between AI capabilities and human relational competencies (Taylor et al., 2025). A major research gap lies in the lack of an adequate, quantitative model to measure the optimal balance point between AI automation and human touch within the specific context of the automotive industry (Lee & Johnson, 2025). Recent experimental studies suggest a dynamic capability configuration approach that adjusts the AI–human ratio based on the stage of the customer lifecycle (Smith et al., 2025), particularly for high-involvement products such as tires and car batteries.

H4: Relationship Marketing plays the role of the mediating variable in the relationship between generative artificial intelligence in marketing and brand value in car tire and battery manufacturing companies.

This suggests a scientific conclusion: technology, no matter how powerful, is merely a means of facilitating human and marketing relationships. The study's integrated model (62.4% explanatory power) provides a roadmap for customer-centric digital transformation. Firms should prioritise AI-enhanced relationship marketing over standalone tech deployment, as human relationships remain the primary conduit for sustainable brand value (Davis & Thompson, 2025). Future research should explore dynamic AI–human collaboration models to refine this paradigm further. Strong relationships transform technological innovation into sustainable market value for the brand. Based on this, the study concludes that integrating artificial intelligence as an independent variable and relationship marketing as an intervening variable is the optimal model for explaining variation in brand value. This model has an overall explanatory percentage of 62.4% and provides surveyed institutions with a clear roadmap for customer-oriented digital transformation.

A key research gap lies in the lack of a contingency model that guides the optimal balance between AI and human involvement, based on customer segmentation and the product lifecycle (Taylor & Anderson, 2025). Recent studies suggest an Adaptive Mediation Threshold Framework that adjusts the intensity of relational mediation based on customer digital readiness and product complexity (Park et al., 2025). These findings reinforce the evolution of the Human–Centric Digital Transformation paradigm in the current literature, which emphasizes that the value of technology is only fully realized through a human relational lens (Zhang et al., 2025).

5. CONCLUSION

This study illuminates one of the most significant contemporary shifts in management and marketing: the strategic role of generative artificial intelligence (AI) in building and strengthening brand value. The study began with the fundamental question of how to translate technological innovations into market value. Through rigorous statistical analysis, the study concluded that technology still requires human and marketing channels to maximize its impact, regardless of its generative power. This is exemplified by the essential intermediary role of relationship marketing.

Field analysis of the study sample revealed a high level of organizational awareness of the importance of adopting smart solutions. Descriptive indicators showed widespread agreement on the effectiveness of these tools. Furthermore, hypothesis testing revealed an integrated relationship model. Although artificial intelligence contributed directly to improving marketing practices, with an explanatory percentage of 54.7%, path analysis showed that building a leading brand truly lies in fostering trust and loyalty with customers via an indirect path. The explanatory percentage for the integrated model increased to 62.4%.

This study's conclusions provide decision-makers and practitioners with a clear roadmap: investing in artificial intelligence should be a strategic means to 'humanize' digital interactions and deepen relationships with consumers, not an end in itself. Brands that successfully leverage machine intelligence to foster warm customer relationships will gain a competitive edge in highly competitive, rapidly evolving digital markets. In conclusion, this study aims to encourage researchers and practitioners to further explore the mediating and moderating variables that influence this dynamic relationship. This will ensure the sustainability of brands' competitive value in the age of artificial intelligence.

6. LIMITATION AND IMPLICATION

Despite its scientific contribution to the definition of the relationship between generative artificial intelligence and brand value, this study's findings are subject to limitations encountered by the researchers during the application phase, which limit their generalisability. First, the study focused solely on 'relationship marketing' as the mediating variable. Other organisational and environmental factors that may play a complementary role in this model were beyond the scope of this research.

In terms of methodology and human resources, the study was limited to a sample of 151 individuals, characterized by specific qualitative features. The vast majority (72.8%) had advanced digital skills, and over a third had more than sixteen years of professional experience. The distinctiveness of this sample may cause the results to reflect a digitally and intellectually mature work environment, which could limit the applicability of these findings to organizations or work environments with a digital divide or lack of experience.

Furthermore, the sample was limited in terms of both space and sector, as it was primarily concentrated in local employment agencies and exclusive agents. Thus, the results reflect the nature of work in the private sector more closely than in other service-oriented or governmental sectors. The temporal limitation related to the technology under investigation should also be noted; generative artificial intelligence is a rapidly evolving field, so the perceptions and findings are confined to the timeframe in which the data was collected.

Finally, relying solely on questionnaires for data collection limits the results to participant self-assessment, which is a well-known methodological limitation of descriptive studies. However, these limitations do not diminish the study's scientific value. Instead, they provide a clear framework for interpreting the results and open up opportunities for future researchers to expand the sample size or explore new sectors to strengthen the proposed model.

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Conflict of Interest Statement: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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